Indian Journal of Science and Technology, *Vol 8(15), 70061, July 2015*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Efficient Segmentation and Classification of Mammogram Images with Fuzzy Filtering

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Abstract

Background: Worldwide and across India breast cancer is the most common cause of cancer deaths in women. Early or timely detection leads to decrease in the mortality rate. Hence, classification of patients based on the size of the tumor/ abnormal masses and less treatment cost must be high priority. **Methods/Statistical Analysis:** In this paper mammogram images are being acquired from real time and standard databases for imaging the suspected patients. The main purposes of the suggested methods are to diagnose the cancer using fuzzy rules with minimum phases in implementation. Important factors were drawn from the images for subsequent investigation and analysis with the help of Fuzzy Enhanced Mammogram Segmentation scheme. The paper presents two methods and is implemented in (i.e. FEM1 and FEM2) Mat lab programming environment. **Results:** The images examined were marked by qualified Radiologist and extracted the images using Photoshop tool. The proposed methodologies were evaluated for real images and Mammographic Image Analysis Society (MIAS) database images consists of 320 images for 160 patients each of 1024x1024 resolutions based gray level images. Based on the results it is found that the CDR for FEM1 is 87% whereas FEM2 demonstrates only 77% and also takes 6.25 times lesser execution time. Radiologists need more precise and reduced processing time making the outcome of FEM1 method more practicable. For the evaluation of performance, statistical properties like Similarity Index (SI), Correct Detection Ratio (CDR), and Under Segmentation Error (USE) are computed. The paper presents computations of segmentation efficiency, enhancement performance and comparative analysis between the method 1 and method 2 in terms of segmentation efficiency and CPU processing time. Finally Support Vector Method is used to classify whether the mammogram under test is normal or abnormal. **Conclusion:** FEM1 outperforms other similar methods. The proposed work provides faster, accurate results and more useful for the diagnosis and classify the abnormal tumors or masses at a cheaper cost.

Keywords: Enhancement, Fuzzy, Image Classification, Image Segmentation, Mammogram, Wavelet

1. Introduction

Detection of abnormal masses in the breast region at the early stage is the key concern for a better treatment. Digital Mammogram is one of the popular techniques to identify breast cancer. Studies have indicated a decline in severe breast cancer and deaths in women who undertake regular mammographic screen[1,2].

Usually the size of these masses is very small hence; there is a need to improve the visibility to the radiologists for correct detection and right diagnosis. Digital image enhancement of mammograms allows additional convincing interpretation of complicated cases without resorting to follow-up patient examinations and other unproductive procedures. This would enable quicker diagnoses of usual cases. Large numbers of negative biopsies encountered in current practice can be minimized if an enhanced mammogram provides a detailed and certain diagnosis[3,4].

Feature extraction relate to diverse statistical quantitative measurements of mammographic images used for decision making process with regard to pathology of a structure or an abnormality. After the features extraction, a portion is selected for most strong features, aiming to improve the classification accuracy and to reduce the overall complexity[5].

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In[6] developed a system for the classification of mammographic masses as malignant or benign by adaptive k-means and Adaptive Neuro Fuzzy Inference Systems (ANFIS) - Learning Vector Quantization (LVQ) method. A classification precision of 86.6% was achieved, and raised it by ANFIS LVQ method to further 87.6% accuracy using back propagation unsupervised learning method in ANFIS. In[7] developed a system to diagnose the breast cancer, using Spherical Wavelet Transform (SWT) to obtain the features of the masses with Support Vector Machines (SVM) for the diagnosis. According to the mass-tissue classification she achieved a 96% of accuracy rate and with a number of the false positives per image as 0.05[8].

In[9,10], an adaptive neighborhood image processing method was used to enhance the contrast of features relevant to mammography. The fundamental idea of this mechanism is to establish a standard of contrast measurement and to improve the image contrast through enhancement. However, this method may enhance noise and digitization effect, for a small neighborhood, and may lose the details when used for a large neighborhood.

The paper is structured as follows. Starts with an introduction, section II discuss about the fuzzy based enhancement approach for the mammogram images, in which two methods were explained. Section III explains about the region extraction process. Section IV offers mathematical formulations for feature extraction. Section V depicts classification method steps for the experiment and section VI presents the results that were obtained using 1 and 2 approaches. A comparative analysis is also been shown to state the performance and simplicity of the approaches ending with the conclusions.

2. Fuzzy Enhanced Mammogram Segmentation (FEMS)

Mammograms may vary in their distribution of gray levels. A few mammograms may be brighter than others due to denser breasts. Normalization is performed before enhancement to allow the uniformity of the intensity ranges for all mammograms. In this paper two fuzzy strategies and their comparison is presented for contrast enhancement of mammogram images.

Fuzzy set theory is being effectively applied to image processing and pattern recognition theories. Fuzzy set theory is a useful tool for handling the uncertainty associated with vagueness. Image processing bears some uncertainty in nature. Moreover, some definitions, such as edges, boundaries and even the definition of contrast are fuzzy. Therefore, it is reasonable to apply fuzzy set theory to contrast enhancement of an image[11–14]. Two methods are mentioned in the paper, the first is considered from the work done by Cheng et al. In[12] with a improvisation which are mentioned in equation (5) and (6), later the method 2 is mentioned involving FIS (Fuzzy Inference System) and depends on the rules of training. Both the algorithms are described below.

2.1 Method 1

The steps involved in the in method 1 are as given below:

(i) Compute the fuzzy membership function.
Let x_{mn} be the intensity level of a gray level Image then

$$\mu_x\left(x_{mn}\right)=\begin{cases} 0 & 0\le x_{mn}\le a \\ \dfrac{\left(x_{mn}-a\right)^2}{(b-a)(c-a)} & a\le x_{mn}\le b \\ 1-\dfrac{\left(x_{mn}-c\right)^2}{(c-b)(c-a)} & b\le x_{mn}\le c \end{cases} \tag{1}$$

(ii) Compute the mean edge value.

$$E_{\mu(x_{mn})}=\sum_{(m,n)\in W_{mn}}\frac{\mu\left(x_{mn}\right)\delta\left(x_{mn}\right)}{\sum_{(m,n)\in W_{mn}}\delta_{\mu}\left(x_{mn}\right)} \tag{2}$$

Formula:

$$L_{max}-\mathrm{L}_{mi}$$

Where L_{min} and L_{max} are the minimum and maximum gray levels of the image.

2.2 Method 2

Where $\delta_{\mu}(x_{mn})$ is the edge value of the image in fuzzy domain obtained by Sobel edge operator.

(iii) Evaluate the contrast

$$C_{\mu(x_{mn})}=\frac{\left|\mu\left(x_{mn}\right)-E_{\mu(x_{mn})}\right|}{\left|\mu\left(x_{mn}\right)+E_{\mu(x_{mn})}\right|} \tag{3}$$

(iv) Intensify or amplify the contrast values.

$$C'_{\mu(x_{mn})}=\left(C_{\mu(x_{mn})}\right)^{\sigma_{mn}} \tag{4}$$

Where σ_{mn} is the amplification factor.

(v) Modify the membership function using modified contrast values.

$$\mu'(x_{mn}) = \begin{cases} \dfrac{E_{\mu(x_{mn})}\left(1 - C'_{\mu(x_{mn})}\right)}{1 + C'_{\mu(x_{mn})}} & if\ \mu(x_{mn}) \le E_{\mu(x_{mn})} \\ \dfrac{E_{\mu(x_{mn})}\left(1 + C'_{\mu(x_{mn})}\right)}{1 - C'_{\mu(x_{mn})}} & if\ \mu(x_{mn}) > E_{\mu(x_{mn})} \end{cases} \quad (5)$$

(vi) Apply De-fuzzification.
Transform the membership function value $\mu'(x_{mn})$ into gray level using the below

2.2.1 FIS (Fuzzy Inference System)

The following are the fuzzy rules implemented for the contrast enhancement in method 2:

- If the pixel intensity is dark then output is darker.
- If the pixel intensity is gray then output is gray.
- If the pixel intensity is bright then output is brighter.

(i) Read an image and apply the fuzzy membership function.

$$\mu_{(xy)} = \exp\left(-\frac{(L\frac{f(x,y)}{s})^2}{2}\right) \quad (7)$$

Where L is the maximum intensity level and S is the variance.
(ii) Obtain the new membership function.

$$\mu'(xy) = \begin{cases} 2*\mu(xy)^2, & if\ \mu(xy) \le 0.5 \\ 1 - 2*(1-\mu(xy))^2, & if\ 0.5 \le \mu(x,y) \le 1 \end{cases} \quad (8)$$

(iii) Obtain the enhanced image as output.

$$f'(x,y) = L - s(\sqrt{-2\log\left(\mu(x,y)\right)}) \quad (9)$$

3. Region Extraction

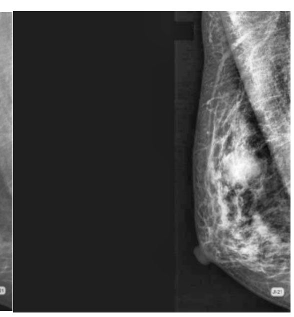
Many of the mammography images have large dark background which creates an obstacle for classification process thereby decreasing the classification rate. A mammogram is divided into three distinctive regions: the breast region, the background (non-breast) region, and the regions of artifacts. The breast region is created when X-ray is absorbed into breast. Background is the region where X-ray has no obstacle. Artifacts are the objects such as labels[15,16]. Background segmentation is useful for computer-aid-system because it significantly reduces the region of interest (Circular or disk shape refer[17]) so that the breast region can be separated from the original image as shown in figure 1.

The following are the steps that are followed in extraction of the breast region.

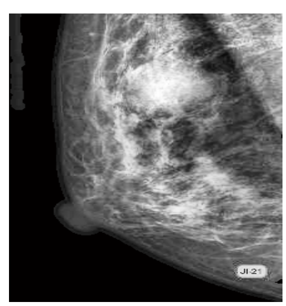
- Apply canny edge detector.
- Consider the disk shape structuring element and dilate the image.
- Fill the holes to create a proper mask.
- Crop the region according to the alignment of mask.

4. Feature Extraction

Selective features are extracted for the mammogram images in transform and spatial domains. Wavelet transform are very useful to represent the high texture content since, the mammogram images do contain high texture and these transforms are utilized for feature extraction.

(a) **(b)**



(c)

Figure 1. **(a)** Original Image, **(b)** Enhanced Image and **(c)** Region extracted Image.

4.1 Wavelet Transform

The basic functions are a set of dilated and translated function[18].

$$\varphi_{j,k}(n) = 2^{\frac{j}{2}} \varphi\left(2^{j} n - k\right) \tag{10}$$

And a set of dilated and translated wavelet function is represented by:

$$\psi_{j,k}(n) = 2^{\frac{j}{2}} \psi\left(2^{j} n - k\right) \tag{11}$$

Where $\varphi_{j,k}(n)$ and $\psi_{j,k}(n)$ are scaling functions and the mother wavelet functions.

The Discrete Wavelet Transform (DWT) can be expressed as:

$$C_j(k) = \sum_{n} C_{j-1}(n) h^{*}(n-2k) \tag{12}$$

$$d_j(k) = \sum_{n} c_{j-1}(n) g^{*}(n-sk) \tag{13}$$

And the reconstruction is as followed as:

$$C_j(k) = \sum_{n} C_{j-1}(n) h^{*}(n-sk) + d_{j-1}(n) g^{*}(n-2k) \tag{14}$$

A square matrix is represented i.e. termed as the co-occurrence matrix with a relative frequencies P(i, j, d,θ) which two neighboring pixels are separated by distance 'd' at orientation θ occur in the image with gray level at (i,j).

4.1.1 Contrast

Is termed as a measure of local variance in the image. This factor is large for the images which has large amount of local variation in gray levels and relatively smaller value for image with uniform gray level distributions[19].

$$C = \sum_{i=1} \sum_{j=1} (i-j)^2 P(i,j)^2 \tag{15}$$

4.1.2 Inverse Difference Moment (IDM)

This reflects the texture changes in the images.

$$IDM = \sum_{i=1} \sum_{j=1} \frac{1}{1+(i-j)^2} p(i,j) \tag{16}$$

4.1.3 Entropy

This provides a measure of complexity of image. Based on the computation it is found that complex textures depicts high level of entropy.

$$S = -\sum_{i=1} \sum_{j=1} p(i,j) \log\left(p(i,j)\right) \tag{17}$$

The features are extracted in the spatial domain as well as in the transform domain. For the transform domain analysis wavelets are considered in this paper. Based upon a certain threshold value of entropy a decision of normal or abnormality is considered. This approach is named as Wavelet based Entropy Method (WEM) in this paper.

5. Classification

In this paper mass classification into benign and malignant is presented based on the statistical and textural features extracted from mass from the breast region using proposed SVM method.

Support Vector Machine (SVM) is a classification mechanism which is broadly used for the diagnosis of breast tumors. SVM amid various learning algorithms is inspired by statistical learning theories 20. The advantage of SVMs is that by choosing a specific hyper plane among many, would divide the data into feature space to minimize the crisis of over fitting the training data. SVMs can be applied on arbitrary distributed features. There are many possible linear classifiers that can divide the data, but there is only one that maximizes the margin. Such linear classifier is named as the optimal separating hyperplane. The standard SVM takes a set of input data and predicts for each given input considering it as a member of two possible classes. Hence, SVM is known as a non-probabilistic binary linear classifier. The basic task for a SVM method is to project data points from a given two class training sets in a higher dimensional space, and then it finds an optimal hyperplane. The optimal one is the one that separates the data with a maximum margin. SVM recognizes the data points close to the optimal separating hyperplane which are termed as support vectors. The distance among the separating hyperplane and the adjacent of the negative and positive data points is termed as the margin of SVM classifier.

Precisely, the idea of SVM is to find the best values for the hyperplane parameters w and b (e.g. w0 and e.g. b0). After finding the optimal separating hyperplane, such as w0·x+b0 = 0, an unseen pattern, x_t, can be classified by the decision rule: f(x) = sign (w0·x+b0).

Whereas x is a vector of the dataset mapped into high dimensional space. Each x_i, as it belongs to one of two classes, has a corresponding value y_i, where

$y_i \in \{1, -1\}$, while w and b are parameters of the hyperplane that the SVM would estimate. The nearest data points to the maximum margin hyperplane lie on the planes:

$$(w \cdot x) + b = +1 \text{ for } y = +1 \text{ and } (w \cdot x) + b = -1 \text{ for } y = -1$$

By rescaling w and b, with no loss in generality, and grouping the above constraints in a single notation:

$\forall i, y_i f(x_i) \geq 1$, Where y = +1 for class w1 and y = −1 for class w2.

The width of the margin is given by m = **2/||w||**.
Following are the steps performing the classification process[21,22].

- Read a mammogram image of size MxN and normalized the image with global histogram equalization.
- As explained in section III extract the breast region where the abnormality is presented.
- Apply wavelet transform and decompose the image into low and high frequency sub bands[23,24].
- Extract the gray level features for the low frequency sub band forming a feature vector.
- Train the RBF based SVM with these features[25].
- The above mentioned steps are repeated for feature extraction and are being tested for different normal and abnormal images.

This approach of abnormality detection is termed as Wavelet based Classifier Method (WCM) in this paper. Two approaches are being used in this paper i.e. Wavelet Entropy based Method (WEM) and Wavelet classifier based Method (WCM) as shown in Table 1.

6. Experimental Results

The proposed methodologies are evaluated for MIAS database images taken from[26], consists of 320 images of 160 patients each of 1024x1024 resolutions based gray level images. For the evaluation of performance, statistical properties like Similarity Index (SI), Correct Detection Ratio (CDR), and Under Segmentation Error (USE) are computed.

6.1 Preparation of Ground Truth Images

In both the experiments real time Digital Breast Tomo synthesis images-DBT and for and Standard database images 26-28 were considered for the evaluation of the algorithm. The ground truth images were marked by an expert (Radiologist) and extracted using Photoshop tool.

6.2 Evaluation Metrics

The results of evaluation of tumor extraction obtained by the proposed method are compared with the manually segmented tumors. The manual segmentations are provided by medical experts, which might include abnormal tissues along with the tumor region. Let us represent 'M' be the manual segmented tumor and 'A' be the segmented tumor by the proposed method as shown in Figure 2. The Similarity Index (SI), Correct Detection Ratio (CDR), Under Segmentation Error (USE) and Over Segmentation Error (OSE) are used for efficiency evaluation. SI is a measure which offers the true segmented region relative to the total segmented region in both the segmentations. CDR value indicates the degree of trueness of the actual tumor. USE is the ratio of the number of pixels falsely identified as tumor portion by the proposed method to the manual segmented tumor. OSE is the ratio of number of pixels falsely identified non tumor region by the proposed method to the manual segmented tumor. Total Segmentation Error (TSE) is the sum of USE and OSE. The evaluation metrics SI, CDR, USE and OSE are obtained by equations (5), (6), (7) and (8) respectively[29,30].

$$SI = \frac{2TP}{2TP + FP + FN} \times 100\%$$

$$CDR = \frac{TP}{TP + FN} \times 100\%$$

$$USE = \frac{FP}{TP + FN} \times 100\% \quad (18)$$

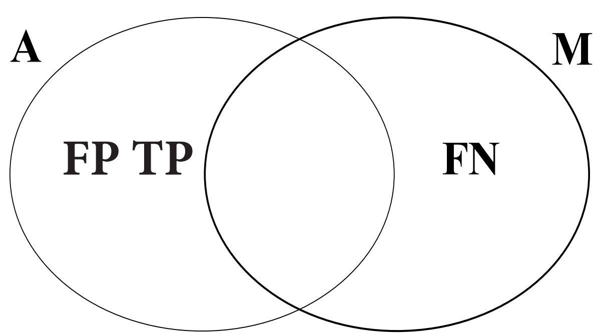
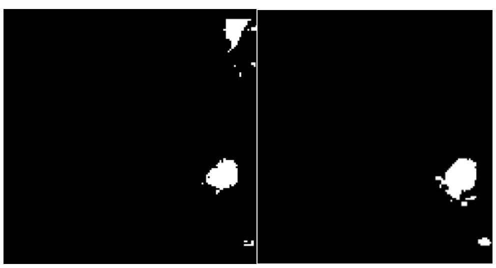


Figure 2. Venn diagram representation of M, A, TP, FP and FN.

Where TP is the number of pixels detected correctly, FP is the number of pixels detected falsely as tumor and FN is the number of pixels detected falsely as non tumor. The experiments were conducted on 120 images out of which few results are presented here. The details of the results are presented below.

6.2.1 Method 1: Results

(a) (b)



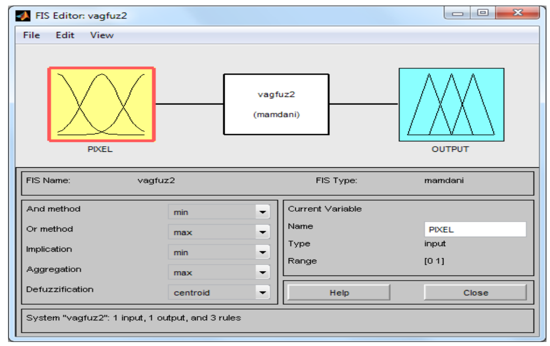
(c) (d)

Figure 3. **(a)** Original Image, **(b)** Enhanced Image with Fuzzy method 1, **(c)** Extracted Abnormal portion and **(d)** Manually Segmented.

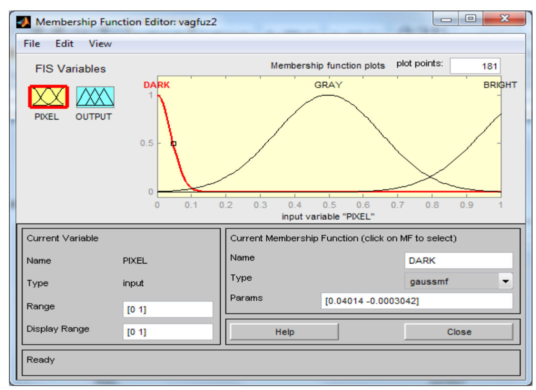
6.2.2 Method 2: Results

In method 2, FIS (Fuzzy Interference System) is designed in Matlab; the following membership function is used for the enhancement process.

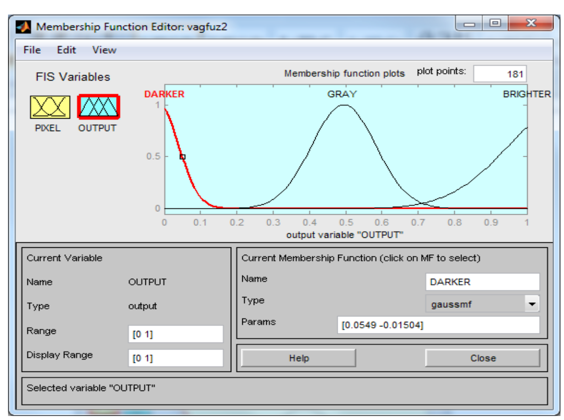
The above figures shows the experimental results that were obtained using both the approaches discussed in this paper. Figure 2, shows the calculations of the segmentation efficiency. Table 1 showcases the outcome of the classification results. Figure 3 depicts the enhancement of the image with the method 1 and also shows the resultant segmented image which is compared against the manual segmented image for the evaluation of the segmentation efficiency. Similarly Figure 5 shows the images that were obtained using method 2. Figure 4 clearly shows the membership function that is designed using FIS (Fuzzy Inference System) in Matlab and the rules that were considered for the method. Figures 6 and 7 shows a comparative analysis between the method 1 and method 2 in terms of segmentation efficiency and CPU processing time. From the experimental analysis it is found that method 2 needs more processing time which is very essential observation when the situation arises with respect to diagnosis. Based on the results obtained it is found that the overall CDR for FEM1 is 87% while FEM2 offers only 77% and also consumes 6.25 times lesser processing time. Radiologists require the results to be more accurate and processed in a very less time apart from this fact, it can be clearly stated that FEM1 is practicable.



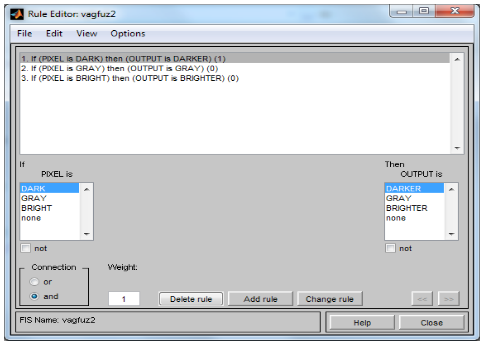
(a)



(b)

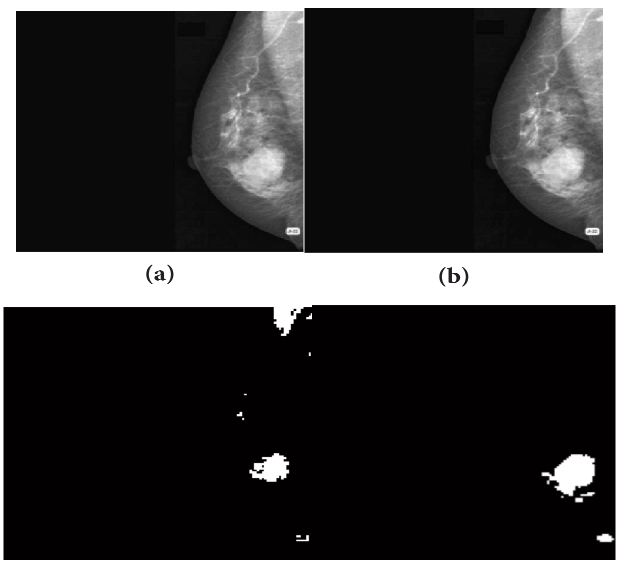


(c)



(d)

Figure 4. **(a)** Membership Function (MF), **(b)** Input Variable of Mf, **(c)** Output Variable of output and **(d)** Fuzzy MF rules.



(a) (b)

(c) (d)

Figure 5. **(a)** Original Image, **(b)** Enhanced Image fuzzy Method 2, **(c)** Extracted abnormal Region and **(d)** manually Segmented Image.

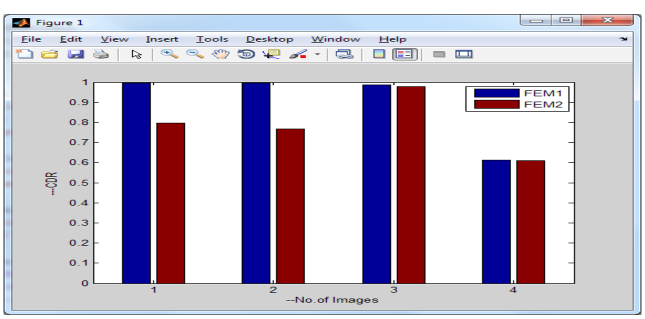


Figure 6. Performance analysis of two methods in terms of Correct Detection Ration (CDR).

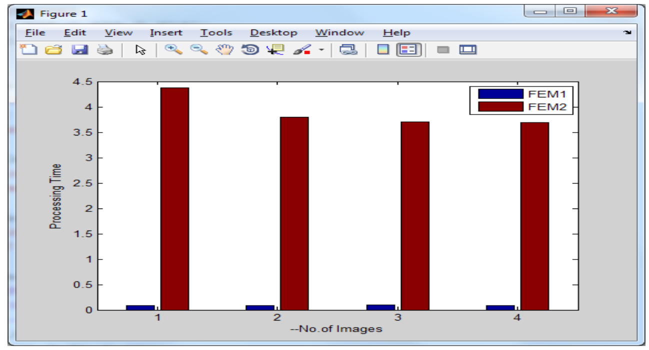


Figure 7. Performance analysis of two methods in terms of CPU time.

Table 1. Experimental results obtained for various images from MIAS database 9

Sl. No.	Image (Manual)	WEM	WCM
1.	Abnormal (mdb001)	Abnormal	Abnormal
2.	Abnormal (mdb002)	Abnormal	Abnormal
3.	Normal (mdb003)	Abnormal	Normal
4.	Normal (mdb004)	Abnormal	Abnormal
5.	Normal (mdb006)	Normal	Normal
6.	Abnormal (mdb005)	Abnormal	Abnormal
7.	Abnormal (mdb010)	Abnormal	Abnormal
8.	Abnormal (mdb012)	Abnormal	Abnormal
9.	Normal (mdb011)	Normal	Normal
10.	Abnormal (mdb015)	Abnormal	Abnormal

7. Conclusion

Fuzzy Enhanced Mammogram (FEM) image segmentation methods are proposed in this paper. The methods are evaluated on a set of images and the performance evaluation is carried out with segmentation efficiency metrics and also with respect to the processing time. From the experimental results it was found that the FEM1 outperforms other similar methods discussed in this paper for almost all the images. Overall CDR for FEM1 is 87% while FEM2 gives 77% and consumes 6.25 times lesser processing time. The proposed work is very fast, accurate and can be more useful for the diagnosis of abnormal tumors or masses. In future this work can be extended for classification, identification.

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